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Joint Goal Human Robot collaboration-From Remembering to Inferring

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Abstract

The ability to infer goals, consequences of one's own and others' actions is a critical desirable feature for robots to truly become our companions-thereby opening up applications in several domains. This article proposes the viewpoint that the ability to remember our own *past* experiences based on *present* context enables us to infer *future* consequences of both our actions/goals and observed actions/goals of the other (by analogy). In this context, a biomimetic episodic memory architecture to encode diverse learning experiences of iCub humanoid is presented. The critical feature is that partial cues from the present environment like objects perceived or observed actions of a human triggers a recall of context relevant past experiences thereby enabling the robot to infer rewarding future states and engage in cooperative goal-oriented behaviors. An assembly task jointly done by human and the iCub humanoid is used to illustrate the framework. Link between the proposed framework and emerging results from neurosciences related to shared cortical basis for 'remembering, imagining and perspective taking' is discussed.

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Keywords: Human robot collaboration, Robot episodic memory, iCub humanoid, internal simulation, Cumulative learning

1 Introduction

From dining together to jointly assembling an IKEA table from constituent parts we are acting and anticipating consequences of potential actions, goals of both, oneself and the other. This seemingly effortless "real-time" inference of others actions/goals and prediction of ensuing future events enables us to both plan our actions accordingly or engage in cooperative goal oriented behaviors. Undoubtedly, as articulated in several recent robotics roadmaps [1, 2] this is a critical desirable feature for robots working alongside humans in unstructured environments- from industry to homes. Even today, most existing approaches in industrial manufacturing involving human robot coexistence is based on each agent performing isolated steps independently with minimal communication exchanged as necessary

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[3]. In this context, recent advances in the design and availability of safe, compliant robots like Baxter, iCub humanoid, Kuka LBR, Universal Robots is gradually enabling humans and robots to share workspaces. This opens up the scope for “joint-goal” human robot scenarios- where both agents act/perceive/plan collaboratively in a continuously evolving unstructured environment (as a simple example, assembling something from constituent parts). Given that, successful collaboration with another agent in a joint goal task requires a complex integration of multiple subsystems like perception, action, goal directed reasoning, we are only beginning to scratch the surface of understanding the computational basis of social intelligence in autonomous robots (see [4] for recent reviews).

This article is an exploration into this topic with the working hypothesis that the ability to remember our own *past* experiences based on *present* context enables us to infer *future* consequences of both our actions/goals and observed actions/goals of the other (by analogy). Emerging trends from neurosciences importantly the discovery of the Default Mode Network (DMN) in the brain [5] is providing converging evidence in this direction. In particular, studies on DMN indicate that there is an extensive overlap in cortical networks activated while remembering the past and those engaged during simulation of the future and adopting the perspective of the other [6-7]. At the core of DMN are the brain areas in the Medial Temporal Lobe known to be involved in episodic memory. Disruption to the DMN also indicates suppressed social behavior as observed in cognitive disorders like ASD [7].

In the context of cognitive robotics and from a computational/functional perspective, presently there is consensus that the central function of DMN is to generate self-referential episodic simulations- that include recall of past experiences, prediction of potential future states and inferring the perspective of the other. Given the trends in neuroscience of memory, computational modelling and implementation of biomimetic robot episodic memory has been a topic of emerging interest in cognitive robotics ([8-9] see, Vernon, Beetz and Sandini, 2015 for a review). Robot episodic memory systems have been instantiated both sub-symbolically using ANNs and symbolically using content-addressable image databases with traditional image indexing and recall algorithms. Importantly, unlike in synthetic systems where memory is usually treated as a passive storage device, this viewpoint looks at memory as an active process involved in forward simulation and presepctive taking.

In this context, we present a growing, multimodal episodic memory framework to encode diverse experiences of the robot acquired cumulatively by interacting with the environment. The central idea is that the episodic memory network is activated autonomously based on diverse partial cues emerging from the environment mainly- a) vision-objects perceived in the present scene; b) linguistic words, for example the word “red ball” or “assemble fuse box”; c) Actions performed by a human counterpart. Partial cues trigger the retrieval dynamics enabling the robot to recall its own past experiences in relation to the present context. We then demonstrate how context specific recall of past episodic experiences based on observation of the actions of a human counterpart enables the robot to simulate future states and engage in cooperative goal directed behaviours. A playful scenario where the robot learns cumulatively through multiple experiences to assemble the tallest possible tower with random object’s and then exploits such knowledge to co-operate with the human to jointly assemble the tallest tower is used to illustrate the results. In sum, the architecture offers shared computational basis for “remembering, imagining and perspective taking” in cognitive robots. As a side effect, since such episodic memories are derived from direct experiences (of the robot), also finesses the symbol grounding problem [10].

The rest of the article is organized as follows. Section 2 describes the central building blocks related to perception, action, robot episodic memory system in the proposed framework. An example iCub humanoid robot learning to assemble a tower suing different objects presented randomly, the ensuing representation in the episodic memory network, the encoding and retrieval dynamics is presented to illustrate the computational model. Section 3 presents results where the iCub humanoid exploits its past experiences to creatively collaborate with a human counterpart assembling a tower. A discussion concludes.

2 From Remembering to Inferring –Central Building blocks

This section describes the main building blocks in the proposed framework for joint goal human robot collaboration (figure 1), developed within the framework of EU funded Darwin project. While the perception-action related building blocks are described only briefly to provide context, the episodic memory storage/retrieval module is described to a greater level of detail.

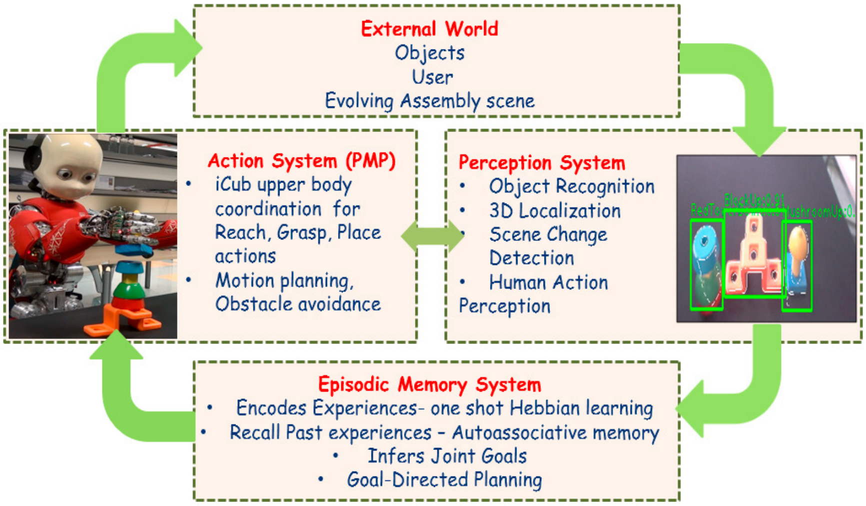

Figure 1. Central building blocks for joint goal human robot collaborative Tower assembly

A. **Perception-Action Loop-** Any action executed by the robot or human in the context of the joint "tower assembly" task constantly changes the scene in the environment. The real time operation and accuracy of the perception-action system is critical for smooth functioning of the system. The perception module consists of several subsystems to detect a) What-objects are present in the scene through shape analysis based on chamfer matching combined with the sliding window technique [6]; b) Where-3D localization of the objects through stereo vision- that both provides spatial coordinates for reach/grasp actions and additional information about relative alignment of the objects (example- block1 is on top of block 2); c) Scene change and Human action detection-when objects in the scene are displaced, not by the robot based on proprioceptive feedback) and recognition of human hand. The action system is based on the Passive Motion Paradigm framework that coordinates the upper body of iCub humanoid (left arm-torso-right arm chain) for reaching, grasping actions [12]. Further details of the organization of Perception-Action loop in Darwin Architecture can be found in [8]. In sum, the perception-action system both enables the robot to learn by interacting and serves as inputs to the episodic memory system to remember, infer and plan potentially rewarding goal directed actions.

B. **Episodic memory system-** The episodic memory network stores multiple experiences of the robot learnt cumulatively by interacting with the environment. While in this specific case we are dealing with the task of assembling a tower with available objects, the memory by itself is task agnostic and store diverse experiences of the robot like learning to push, assembly tasks [13]. The episodic memory network is based on auto-associative neural network [14, 8] and consists of 1000 neurons characterized by "all to all" connections and organized in a sheet like structure with 20 rows each containing 50 neurons (figure 2a). Every row may be thought as an event in time in our case- object recognized, action executed, action recognized, received reward. The complete structure forms an episode of experience. For example, picking up a color tower and placing it on the meccano block: form episodic memory 1. Multiple experiences can be stored into the same network by updating the weights T_{ij} between the neurons using Hebbian learning [8]. A the same time partial cues from the environment- like objects recognized, actions recognized can trigger recall of past experiences using the retrieval dynamics described by equation 1- where Vi is the activity in i^{th} neuron, T_{ij} the weight, I_{inhib} threshold []. The central idea is that such recall of past experiences also enables the robot to infer future rewarding states and thereby engage in joint goal behavior. In other words, our own experiences recalled from memory enables us to infer others actions/goals. To gain experience the robot interacts cumulatively with multiple objects like color tower, red block, meccano block, mushroom and assembling the tallest possible tower suing them (figure 2) as will be described in the next section.

$$\tau_{rel}\dot{V}_k = -V_k + \sum_{j=1}^{N} T_{k,j}V_j + I_{inhib} \tag{1}$$

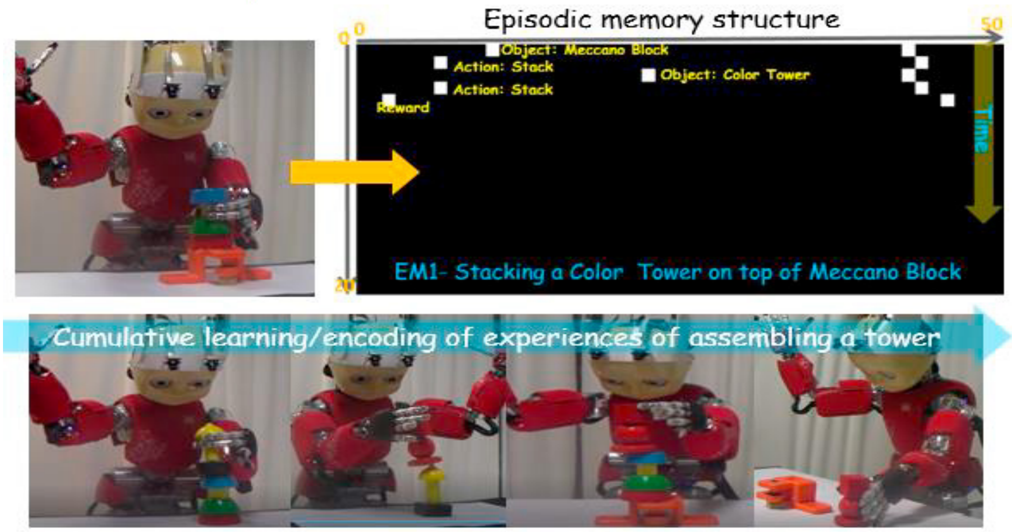

Figure 2. Shows examples of the robot cumulatively gaining experience of assembling the tallest tower by interacting with available objects. Such experiences are encoded into the episodic memory - a fully connected network of 1000 neurons organized in the form of a 20x50 sheet. Every row may be thought as an event in time in our case- object recognized, action executed, action recognized, received reward. For example, picking up a color tower and placing it on the meccano block: form episodic memory 1 (EM1). Multiple experiences (max-230) can be stored in the same auto associative memory.

3 Stacking up a Tower with a Human Counterpart

Akin to experimental tasks in the developmental psychology literature, we choose a playful task of building a tower of objects to test our model. In the first experience (EM1), the robot is presented with two objects, a Meccano Block and a Color Tower (figure 2) and is issued a user goal “Stack”. This user-goal and the two objects perceived act as partial cues to trigger recall of any past experiences. However, in the beginning there are no learnt/past experience, nothing is recalled. With only option to explore, the robot picks randomly the Color Tower to stack on the Meccano Block and does so successfully to get a reward (equal to the number of the objects stacked successfully). The robot encodes this experience in the episodic memory for future recall. In a similar next experience (EM2), the robot stacks two objects, a Mushroom on a Color Tower and this experience is again encoded into memory. In the present case, 9 different experiences with different combinations of objects randomly presented were acquired and stored in the auto associative episodic memory network.

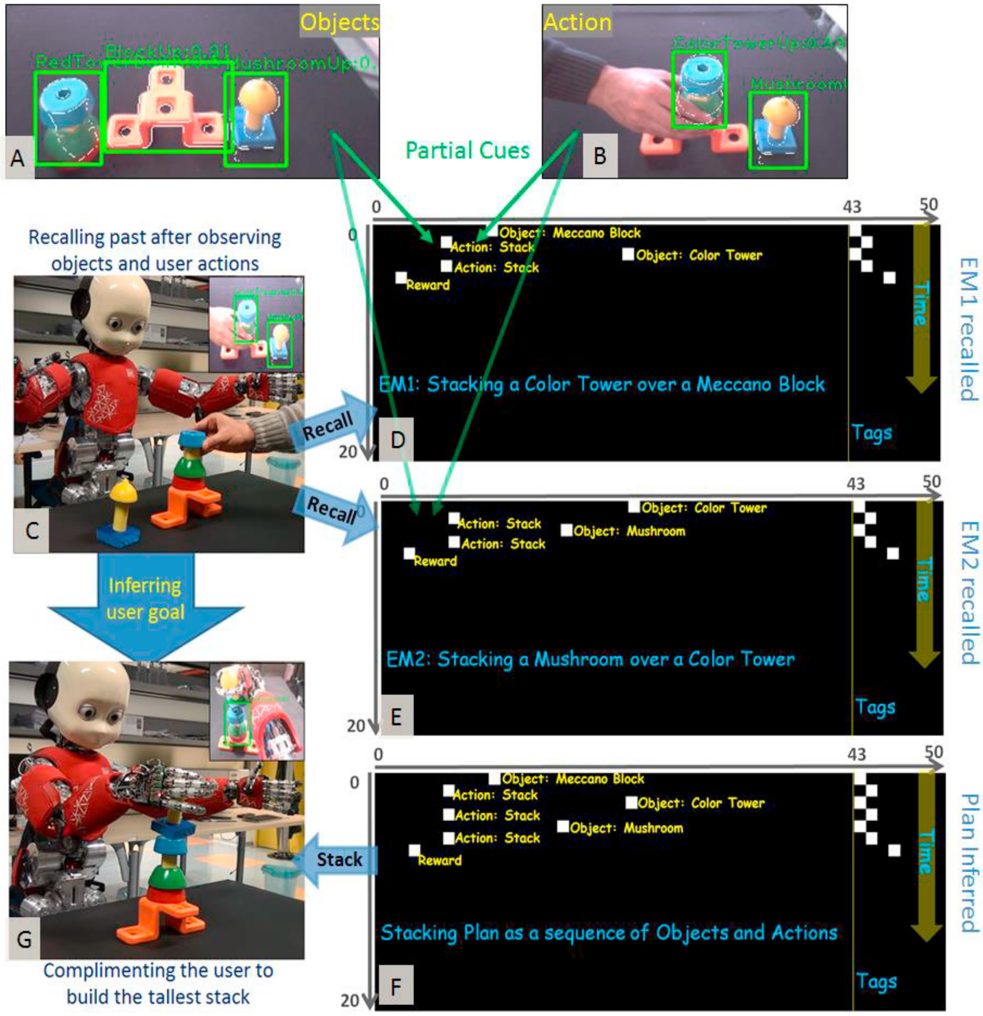

Figure 3: Panel A,B show results of perceptual analysis, through which objects and actions are recognized which act as partial cues. After observing objects and user-action (panel A-C), the robot recalls episodes EM1(panel D) & EM2 (panel E), merges them to infer that it has to continue stacking; forms a plan for stacking (panel F) and executes it (panel G).

In the final stage of the task, three objects i.e. Meccano Block and Color Tower and the Mushroom are available in the scene. *No linguistic user-goal is provided. However, the system observes the user stacking the Color Tower over the Meccano Block*. Hence, the observed user-action of stacking and the objects present in the scene now serve as partial cues to recall the past-experiences that involved performing the same action. As seen in figure 3, the robot recalls two different experiences (EM1 & EM2). Finding a common object i.e. the Color Tower between the two experiences, the system combines the two episodic memories together to generate a novel plan (that it would execute if it were to build the tower). Note that, the generated plan from past experiences also directly leads to the inference of the rewarding future state i.e. placing the mushroom on top of the partially assembled tower in the scene. The robot now executes its own action of stacking the mushroom on top of the color tower, thus jointly completing the assembly with the human.

4 Discussion

While there is converging evidence from neurosciences that cortical areas involved in remembering the past are also engaged in simulating the future and adopting the perspective of the other, the underlying computational basis is blurred. This article presented a biomimetic framework where recalled episodic memories of the robot enable it to simulate future rewarding states and collaborate with the human counterpart to jointly assemble a tower. The central idea is that we reuse our own episodic experiences to infer others actions, consequences of such actions. This critically both enables us to cooperate in joint goals or plan our own future actions based on the present environment. This is a highly desirable feature for future robot companions inhabiting natural living spaces -industrial manufacturing, homes and offices, elderly care to mention a few. While in the preliminary experiment we only considered one joint goal (i.e. assembly of the tower with available objects), work is ongoing to infer multiple possible goals. This is interesting given that different actions with the same object can lead to realization of different user goals. For example, if the human put the color tower into a bin, the goal is to clean up the table, but if he placed it on top of a block the goal could be to build a tower. Further, more complex joint assembly scenarios with the human and humanoid involving more complex actions (like use of tools) will be explored in the future.

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